Predicting the Warpage of Plastic Products during the Injection Molding Process using the BBM Method

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ABSTRACT

During the injection molding process, the warpage prediction plays a significant role in order to improve the quality of a product. This procedure depends on a variety of parameters, such as pressure, melting temperature, packing, and filling time. Polyethylene Terephthalate Glycol (PETG) is a thermoplastic material that exhibits a great bending attribute, heat resistance, and durability. This paper examines a method for predicting the warpage defect using the Box-Behnken Method (BBM). The mathematical model is formed to predict the warpage with high reliability, resulting in R-Sq of 97.81%, R-Sq(adj) of 95.26%, and R-Sq(pred) of 87.39%. The optimal processing parameters are a packing time of 5.5 s, a melting temperature of 270 °C, an injection pressure of 217.4 MPa, and a filling time of 0.8 s. The results show that the proposed method is effective in processing engineering problems related to the prediction and optimization of manufacturing systems for improving sustainability and product quality.

Keywords-PETG; injection molding; Response Surface Methodology (RSM); processing parameters; warpage; optimization

I. INTRODUCTION

Warpage prediction involves Injection Processing Parameters (IPP), such as pressure, melting temperature, packing, and filling time. PETG can be used to produce many plastic parts, such as electrical components, industrial equipment, automotive industry segments, consumer goods, and aerospace applications [1, 2]. PETG is a thermoplastic material with excellent flexural strength, heat resistance, and durability properties [3], used in plastic processing technologies, such as molding, extrusion, and 3D printing [4-6]. Product quality can be improved by eliminating the defects that often occur during the injection molding process. These involve weld lines, shrinkage, and warpage [7, 8]. A great amount of research has been carried out on the detection of methods and techniques to enhance product quality, such as deploying Particle Swarm Optimization (PSO) to improve the performance of a photovoltaic microgrid system [9], applying Artificial Intelligence (AI) to enhance the performance of a cellular network [10], and deploying the Artificial Neural Network (ANN) and Genetic Algorithm (GA) models to improve product quality during the injection molding process [11]. Furthermore, the Neural Network (NN) monitoring model and regression technique were utilized for predicting the surface roughness of the milling process by analyzing the cutting condition [12]. The Taguchi method was employed for optimizing the Processing Parameters (PP) to reduce the warpage and shrinkage of the molded products [13, 14], The Design of Experiments (DoE) method and response analysis technique have been utilized to optimize the PP of hot-rolled steel, and thus improve the mechanical properties of tensile strength and yield strength [15]. Additionally, the kriging model was implemented to optimize the warpage defect of the final product [16]. BBM is an effective probability analysis technique used to solve engineering problems, such as improving efficiency, reducing cost, saving time [17-20], and optimizing an extraction system [21]. The BBM is more efficient than other methods, like the three-level factorial and central composite arrays [22]. The BBM has the greatest ability to collect independent parameters in a group and optimize the objectives of manufacturing systems. The selection of the processing conditions to improve the performance of the manufacturing processes can be achieved by using BBM. The latter can be deployed to optimize the industrial wastewater analyzing the treatment PP [23], to improve a phenolic extraction system [24], to optimize the reservoir fine by affecting factors of concentration, time, salinity, and pH [25], and to improve the dissolution for nanoemulsifying delivery [26].

This paper proposes a method for predicting warpage employing BBM, as an effective way to optimize technical PP, and so improve product quality criteria for manufacturing processes.

II. EXPERIMENT PROCEDURE

Regarding PETG mechanical properties, it has a density of 1270 kg/m3 and a shrinkage rate of 0.2% - 0.5% [27]. The PP has a melt temperature ranging from 220 C to 290 C, a mold temperature ranging from 10 C to 30 C, and an injection pressure ranging from 30 MPa to 130 MPa [28]. Figure 1(a) presents the product's anterior aspect, indicating a thickness of 2.5 mm. Figure 1(b) shows the product's bottom view and its dimensions, including a length of 150 mm and a width of 90 mm. Figure 1(c) presents the isometric view of the product. Table I displays the Box-Behnken (BB) design, including PPs such as melting temperature (*A*), injection pressure (*B*), packing time (*C*), and filling time (*D*), and their levels. The experiments were performed using an Easy Fill Advanced tool, by recording warpages and inserting them into the design table, which expresses the relationship between the warpage of the product and PP. The BBM-based RSM follows the steps of process preparation, BBM modeling, process simulation, function creation, process optimization, and optimization design acquisition, as depicted in Figure 2 [29]. The polynomial model deployed is [30]:

$$Min.Y = a_0 + a_1x_1 + a_2x_2 + a_3x_3 + a_{11}x_{12} + a_{22}x_{22} + a_{33}x_{33} + a_{12}x_1x_2 + a_{13}x_1x_3 + a_{23}x_2x_3 \quad (1)$$

where *Min.Y* is the minimum warpage, a_0 is a constant, x_i is the processing parameter, a_i are the linear coefficients, and a_{ij} are the cross-product coefficients.

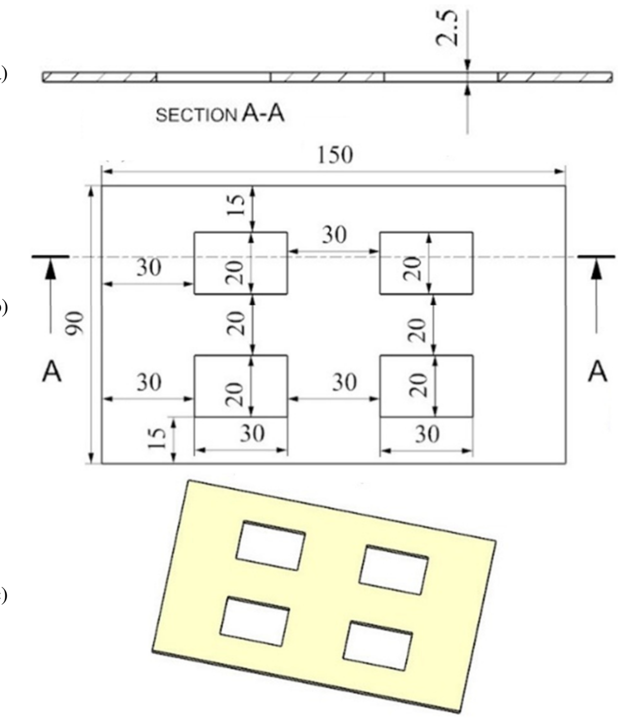

Fig. 1. Detailed drawings of the product: (a) anterior aspect, (b) bottom view, (c) isometric view.

TABLE I. THE BB DESIGN

Injection parameters	Unit	Symbol	Level and value		
			-1	0	1
Melt temperature	ºC	*A*	270	280	290
Injection pressure	MPa	*B*	200	220	240
Packing time	s	*C*	5.5	6.5	7.5
Filling time	s	*D*	0.8	1.1	1.4

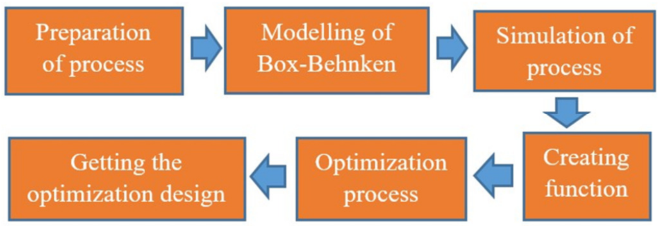

Fig. 2. RSM flowchart.

III. RESULTS AND DISCUSSION

Experiments were performed using the Easy Fill Advanced tool. The warpage was analyzed and simulated under injection molding conditions designed by BBM (Figure 3), in an attempt to minimize warpage tracing on the molded part during the process. Table II presents the BB design table with the coded factors, while Table III shows the BB arrangement and the warpage outcomes documented through warpage analysis. The coded coefficients of the BB analysis of the response surface regression of the warpage, along with the effective parameters of the injection pressure, melt temperature, packing time, and filling time are presented in Table IV.

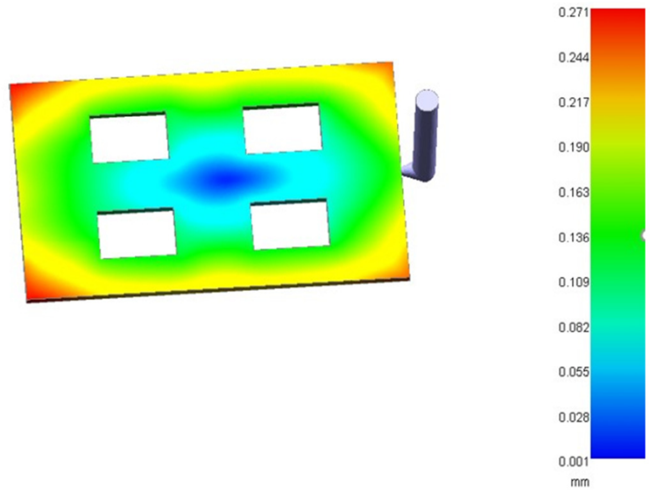

Fig. 3. The warpage result from Easy Fill Advanced software.

TABLE II. BB DESIGN WITH CODED FACTORS

StdOrder	RunOrder	PtType	Blocks	*A* (°C)	*B* (MPa)	*C* (s)	*D* (s)
1	1	2	1	-1	-1	0	0
24	2	2	1	0	1	0	1
16	3	2	1	0	1	1	0
27	4	0	1	0	0	0	0
4	5	2	1	1	1	0	0
7	6	2	1	0	0	-1	1
5	7	2	1	0	0	-1	-1
21	8	2	1	0	-1	0	-1
20	9	2	1	1	0	1	0
26	10	0	1	0	0	0	0
8	11	2	1	0	0	1	1
18	12	2	1	1	0	-1	0
15	13	2	1	0	-1	1	0
9	14	2	1	-1	0	0	-1
12	15	2	1	1	0	0	1
6	16	2	1	0	0	1	-1
25	17	0	1	0	0	0	0
3	18	2	1	-1	1	0	0
10	19	2	1	1	0	0	-1
23	20	2	1	0	-1	0	1
13	21	2	1	0	-1	-1	0
14	22	2	1	0	1	-1	0
17	23	2	1	-1	0	-1	0
19	24	2	1	-1	0	1	0
2	25	2	1	1	-1	0	0
11	26	2	1	-1	0	0	1
22	27	2	1	0	1	0	-1

The model summary of response surface analysis with high reliability criteria of the R^2 of 97.81% and the R^2_{adj} of 95.26% is shown in Table V:

$$R^2 = 1 - \frac{SS_R}{SS_T} \quad (2)$$

$$R^2_{Adj} = 1 - (1 - R^2)\frac{n-1}{n-p} \quad (3)$$

where SS_R is the residual sum of the squares, SS_T is the total sum of the squares, n is the observation of the dependent variable and p is the predictor.

TABLE III. EXPERIMENT DESIGN TABLE AND VALUES

StdOrder	RunOrder	PtType	Blocks	*A* (°C)	*B* (MPa)	*C* (s)	*D* (s)	Warpage (mm)
1	1	2	1	270	200	6.5	1.1	0.263
24	2	2	1	280	240	6.5	1.4	0.271
16	3	2	1	280	240	7.5	1.1	0.267
27	4	0	1	280	220	6.5	1.1	0.268
4	5	2	1	290	240	6.5	1.1	0.275
7	6	2	1	280	220	5.5	1.4	0.271
5	7	2	1	280	220	5.5	0.8	0.265
21	8	2	1	280	200	6.5	0.8	0.265
20	9	2	1	290	220	7.5	1.1	0.272
26	10	0	1	280	220	6.5	1.1	0.268
8	11	2	1	280	220	7.5	1.4	0.27
18	12	2	1	290	220	5.5	1.1	0.276
15	13	2	1	280	200	7.5	1.1	0.267
9	14	2	1	270	220	6.5	0.8	0.258
12	15	2	1	290	220	6.5	1.4	0.275
6	16	2	1	280	220	7.5	0.8	0.266
25	17	0	1	280	220	6.5	1.1	0.268
3	18	2	1	270	240	6.5	1.1	0.263
10	19	2	1	290	220	6.5	0.8	0.27
23	20	2	1	280	200	6.5	1.4	0.271
13	21	2	1	280	200	5.5	1.1	0.269
14	22	2	1	280	240	5.5	1.1	0.269
17	23	2	1	270	220	5.5	1.1	0.263
19	24	2	1	270	220	7.5	1.1	0.261
2	25	2	1	290	200	6.5	1.1	0.276
11	26	2	1	270	220	6.5	1.4	0.264
22	27	2	1	280	240	6.5	0.8	0.265

TABLE IV. CODED COEFFICIENTS OF BBM ANALYSIS

Term	Coef	SE Coef	95% CI	*T*-Value	*P*-Value	VIF
Constant	0.268000	0.000579	(0.266738, 0.269262)	462.59	0.000	
A	0.006000	0.000290	(0.005369, 0.006631)	20.71	0.000	1.00
B	-0.000083	0.000290	(-0.000714, 0.000548)	-0.29	0.779	1.00
C	-0.000833	0.000290	(-0.001464, -0.000202)	-2.88	0.014	1.00
D	0.002750	0.000290	(0.002119, 0.003381)	9.49	0.000	1.00
A×A	0.000000	0.000435	(-0.000947, 0.000947)	0.00	1.000	1.25
B×B	0.000625	0.000435	(-0.000322, 0.001572)	1.44	0.176	1.25
C×C	0.000000	0.000435	(-0.000947, 0.000947)	-0.00	1.000	1.25
D×D	-0.000625	0.000435	(-0.001572, 0.000322)	-1.44	0.176	1.25
A×B	-0.000250	0.000502	(-0.001343, 0.000843)	-0.50	0.627	1.00
A×C	-0.000500	0.000502	(-0.001593, 0.000593)	-1.00	0.339	1.00
A×D	-0.000250	0.000502	(-0.001343, 0.000843)	-0.50	0.627	1.00
B×C	0.000000	0.000502	(-0.001093, 0.001093)	0.00	1.000	1.00
B×D	0.000000	0.000502	(-0.001093, 0.001093)	0.00	1.000	1.00
C×D	-0.000500	0.000502	(-0.001593, 0.000593)	-1.00	0.339	1.00

Table VI portrays the Analysis of Variance (ANOVA) results for the parameter contribution to warpage. These are: $A = 78.26\%$, $B = 0.02\%$, $C = 1.51\%$, and $D = 16.44\%$.

TABLE V. ANALYSIS MODEL SUMMARY

S	R^2	R^2_{adj}	PRESS	R^2_{pred}	AICc	BIC
0.0010035	97.81%	95.26%	0.0000696	87.39%	-231.70	-265.37

Figure 4 shows the Pareto chart analyzed by BBM, with the influence levels of PP lying in the downward trend of melting temperature, filling time, packing time, and injection pressure. Figure 5 demonstrates the warpage distribution, analyzed by BBM and following the normal distribution, with a P-value of 0.819.

Figure 6 illustrates the main effect plot for warpage, with the ranking of *A*, *D*, *C*, and *B* exhibiting a downward trend regarding the influence level on warpage. Figure 7 presents the optimal analysis using BBM, including *A* = 270 °C, *B* = 218 MPa, *C* = 5.5 s, and *D* = 0.8 s. The predicted warpage is 0.258 mm for the above optimal PP set.

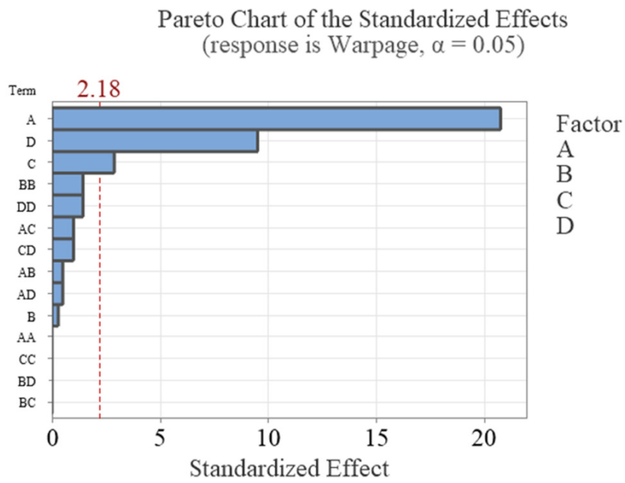

Fig. 4. The Pareto chart of the factor effects on warpage.

TABLE VI. ANOVA RESULTS

Source	DF	Seq *SS*	Contribution	Adj *SS*	Adj *MS*	*F*-Value	*P*-Value
Model	14	0.000540	97.81%	0.000540	0.000039	38.30	0.000
Linear	4	0.000531	96.23%	0.000531	0.000133	131.88	0.000
A	1	0.000432	78.26%	0.000432	0.000432	429.02	0.000
B	1	0.000000	0.02%	0.000000	0.000000	0.08	0.779
C	1	0.000008	1.51%	0.000008	0.000008	8.28	0.014
D	1	0.000091	16.44%	0.000091	0.000091	90.12	0.000
Square	4	0.000006	1.13%	0.000006	0.000002	1.55	0.250
A×A	1	0.000000	0.00%	0.000000	0.000000	0.00	1.000
B×B	1	0.000004	0.71%	0.000002	0.000002	2.07	0.176
C×C	1	0.000000	0.05%	0.000000	0.000000	0.00	1.000
D×D	1	0.000002	0.38%	0.000002	0.000002	2.07	0.176
2-Way interaction	6	0.000003	0.45%	0.000003	0.000000	0.41	0.856
A×B	1	0.000000	0.05%	0.000000	0.000000	0.25	0.627
A×C	1	0.000001	0.18%	0.000001	0.000001	0.99	0.339
A×D	1	0.000000	0.05%	0.000000	0.000000	0.25	0.627
B×C	1	0.000000	0.00%	0.000000	0.000000	0.00	1.000
B×D	1	0.000000	0.00%	0.000000	0.000000	0.00	1.000
C×D	1	0.000001	0.18%	0.000001	0.000001	0.99	0.339
Error	12	0.000012	2.19%	0.000012	0.000001		
Lack-of-fit	10	0.000012	2.19%	0.000012	0.000001		
Pure error	2	0.000000	0.00%	0.000000	0.000000		
Total	26	0.000552	100.00%				

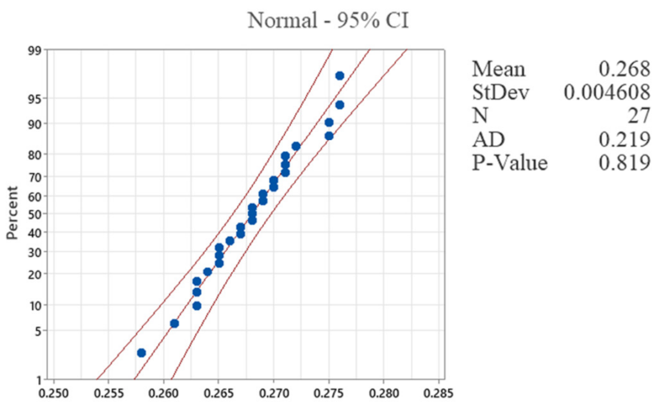

Fig. 5. Distribution of the warpage results.

Fig. 6. The main effect plot for warpage.

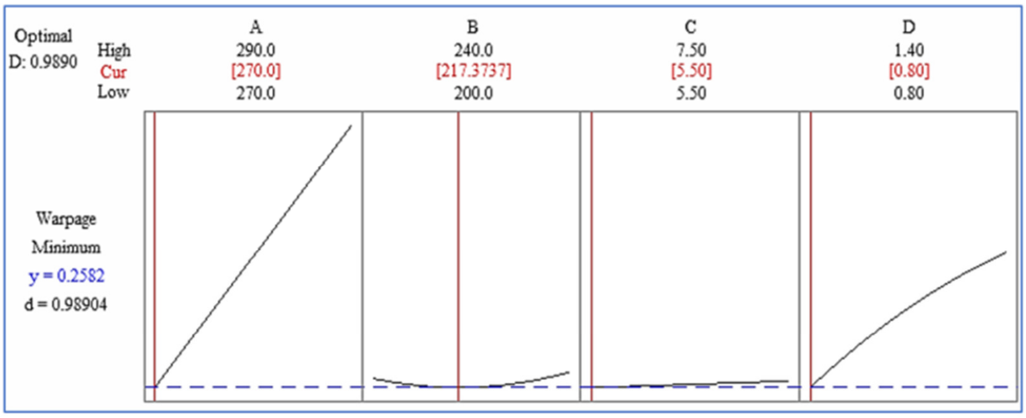

Fig. 7. Optimization analysis result by BBM.

The prediction model for the distortion response by BBM is formed by (2) and the mathematical model has high reliability criteria of R^2 = 97.81% and R^2_{adj} = 95.26%:

$$Warpage = -0.042 + 1.29A \times 10^{-3} - 0.342B \times 10^{-3} + 15C \times 10^{-3} + 58.6D \times 10^{-3} + 0.2B \times B \times 10^{-5} - 6.94D \times D \times 10^{-3} - 0.1A \times B \times 10^{-5} - 5A \times C \times 10^{-5} - 8.3A \times D \times 10^{-5} - 0.00167C \times D \quad (4)$$

IV. CONCLUSIONS

Defect prediction is the essential solution during injection molding to improve product quality, which usually involves Injection Processing Parameters (IPP), such as melting temperature, pressure, packing, and filling time. Polyethylene Terephthalate Glycol (PETG) is a plastic material with good characteristics of heat resistance, bending, and durability. This paper examines a method for predicting warpage using the Box-Behnken Method (BBM). The mathematical prediction model is designed to predict the warpage with the reliability of 97.81%, with high coefficient results, namely R^2 = 97.81% and R^2_{adj} = 95.26%. The optimal processing parameters are a packing time of 5.5 s, melting temperature of 270 °C, injection pressure of 217.4 MPa, and filling time of 0.8 s. The results reveal that the product quality is improved by reducing defects via using the optimization technique tool, controlling the Processing Parameters (PP) during manufacturing processes.

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